RUSSIAN - ARMENIAN UNIVERSITY

Master Program

MACHINE LEARNING

MODULE DESCRIPTION

Professional Cycle (64 ECTS credit points)

Continuous Mathematical Models

Lecturer: Prof. Dr. Garnik Karapetyan
Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (graded)
Standard Studies Period: 2 years

Course description: A course aimed at the construction, simplification, analysis, interpretation and evaluation of mathematical models that shed light on problems arising in the physical and social sciences. Derivation and methods for solution of model equations, heat conduction problems, simple random walk processes, simplification of model equations, dimensional analysis and scaling, perturbation theory, and a discussion of self-contained modular units that illustrate the principal modeling ideas. Students will normally be expected to develop a modeling project as part of the course requirements.

Recommended literature:

1. G.I. Marchuk. Mathematical modeling in the environmental problem .- M., Nauka, 1982
2. G.I. Marchuk. Methods of computational mathematics .- M., Nauka, 1989
3. V. Volterra. Mathematical theory of the struggle for existence .- M., Nauka, 1976
4. Yu.M. Svirizhev, D.O. Logofet. Stability of biological communities .- M., Nauka, 1978
5. L.A. Petrosyan, V.V. Zakharov. Introduction to mathematical ecology .- M., Nauka, 1986
6. O.V. Besov, V.P. Ilyin, S.M. Nikolsky. Integral representations of functions and embedding theorems.-M., Nauka, 1975
7. V.S. Of the world. Equations of mathematical physics.-M., Nauka, 1971.
8. L. HERMANDER. Linear differential operators with partial derivatives. - M., Mir, 1965.
9. L. HERMANDER. Analysis of linear partial differential operators, vol.1 (Theory of distributions and Fourier analysis) .- M., Mir, 1986.
10. V.S. Vladimirov. Generalized functions in mathematical physics.-M., Nauka, 1979.

Introduction to Machine Learning

Lecturer: Dr. Aram Baghiyan
Labor intensity: 2 ECTS, 72 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: Machine learning studies the question "how can we build computer programs that automatically improve their performance through experience?" This includes learning to perform many types of tasks based on many types of experience. For example, it includes robots learning to better navigate based on experience gained by roaming their environments, medical decision aids that learn to predict which therapies work best for which diseases based on data mining of historical health records, and speech recognition systems that lean to better understand your speech based on experience listening to you.This course is designed to give PhD students a thorough grounding in the methods, theory, mathematics and algorithms needed to do research and applications in machine learning. The topics of the course draw from machine learning, from classical statistics, from data mining, from Bayesian statistics and from information theory. Students entering the class with a pre-existing working knowledge of probability, statistics and algorithms will be at an advantage, but the class has been designed so that anyone with a strong numerate background can catch up and fully participate.

Recommended literature:

1. *Machine Learning: a Probabilistic Perspective*, Kevin Murphy.
2. *Pattern Recognition and Machine Learning*, Chris Bishop.
3. *Machine Learning*, Tom Mitchell.
4. *Information Theory, Inference, and Learning Algorithms* , David Mackay.

Algorithms and information security

Lecturer: Prof. Dr. Rafik Tonoyan
Labor intensity: 4 ECTS, 144 academic hours
Form of final control: exam (graded)
Standard Studies Period:2 years

Course description:1.Recursive algorithms. 2. Computable functions. Solvable and enumerable sets. 3. Algorithmically insoluble problems. 4. The 10th problem of Hilbert. 5. Probabilistic algorithms. 6. Hashing. 7. Introduction to the theory of algorithms and examples. 8. Complexity of algorithms. 9. Linear Programming.

Recommended literature:

1. William Stallings. Cryptography and Network Security, 7th edition, Pearson, 2016.

Discrete stochastic models

Lecturer: Dr. Linda Kachaturyan
Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (graded)
Standard Studies Period: 2 years

Course content: The main purpose of this course for muster students is to demonstrate on various examples the power and generous possibilities of probabilistic methods applied to problems from different areas of mathematics.
The course consists of three main parts. The first part contains preliminary facts from probability theory including general discrete probability model, model of sequence of independent trials and Markov scheme (Markov chains). All these material is accompanied by practical examples.
The second part is dedicated to application of probabilistic methods in graph theory, combinatorics, Ramsey theory and extreme theory of sets. We demonstrate on various examples how to use probabilistic methods to obtain deterministic assertions. Generally such statements are existence theorems, but we also demonstrate how probabilistic approach gives an opportunity to create (deterministic) algorithms of finding objects which existence are proved.
In the third part of this course the mathematical theory of communication (Shannon's information theory) is expound. The notion of entropy and its properties are considered. The source coding theorems are discussed both for uniform and variable-length coding. The Shannon's theorems of optimal information transmission in discrete channels without memory are proved.

Recommended literature:

1. Parzen, E. (1962) Stochastic Processes, Holden-Day.
2. Dodge, Y. (2006) The Oxford Dictionary of Statistical Terms, OUP.

Numerical methods and optimization

Lecturer: Prof. Dr. Yuri Hakobyan
Labor intensity: 4 ECTS, 144 academic hours
Form of final control: exam (graded)
Standard Studies Period: 2 years

Course description: Numerical methods are an important branch in Applied Mathematics. It aims at numerically solving all kinds of mathematical problems which arise from practical applications and can be modelled by different mathematical equations or inequalities, for example, linear or nonlinear differential equations and integral equations.
Course prerequisite:
Most fundamental: advanced calculus and linear algebra.

The course is focused on both numerical methods and numerical analysis. And mathematicalanalysis is needed for nearly every numerical method to be introduced. So students should bevery solid in analysis, and have a very good feeling and understanding of numerical methodsand rigorous mathematical reasoning.

Recommended literature:

1. V.M. Verzhbitsky. Fundamentals of numerical methods.-M .: Higher School, 2002.
2. D. Watkins. Fundamentals of matrix calculations. - Moscow: BINOM. Laboratory of Knowledge, 2006.
3. D.V. Beklemishev. Additional chapters of linear algebra. - Moscow: Nauka, 1983.
4. D. Kincaid and W. Cheney. Numerical Analysis: Mathematics of Scientific Computing.- Brooks / Cole Publishing Company, 1991.

Mathematics for Machine Learning

Lecturer: Prof. Dr. Yuri Hakobyan
Labor intensity: 6 ECTS, 216 academic hours
Form of final control: exam (graded)
Standard Studies Period: 2 years

Course description: Broadly speaking, Machine Learning refers to the automated identification of patterns in data. As such it has been a fertile ground for new statistical and algorithmic developments. The purpose of this course is to provide a mathematically rigorous introduction to these developments with emphasis on methods and their analysis.

Recommended literature:

1. "The Elements of Statistical Learning" by Hastie, Tibshirani, and Friedman. Comprehensive but superficial coverage of all modern machine learning techniques for handling data. Introduces PCA, EM algorithm, k-means/hierarchical clustering, boosting, classification and regression trees, random forest, neural networks, etc. ...the list goes on.
2. "Computer Age Statistical Inference: Algorithms, Evidence, and Data Science" by Hastie and Efron.
3. "Pattern Recognition and Machine Learning" by Bishop.
4. "Bayesian Reasoning and Machine Learning" by Barber.
5. "Probabilistic Graphical Models" by Koller and Friedman.

Data Mining

Labor intensity: 2 ECTS, 72 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: The Data Mining programme focuses on modern developments at the intersection of statistics, artificial intelligence and database management. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Aside from the raw analysis step, it involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

Recommended literature:

1. "Data Mining Curriculum". ACM SIGKDD. 2006-04-30. Retrieved 2014-01-27.
2. Clifton, Christopher (2010). "Encyclopædia Britannica: Definition of Data Mining". Retrieved 2010-12-09.
3. Hastie, Trevor; Tibshirani, Robert; Friedman, Jerome (2009). "The Elements of Statistical Learning: Data Mining, Inference, and Prediction". Retrieved 2012-08-07.
4. Fayyad, Usama; Piatetsky-Shapiro, Gregory; Smyth, Padhraic (1996). "From Data Mining to Knowledge Discovery in Databases" (PDF). Retrieved 17 December 2008.
5. Han, Jiawei; Kamber, Micheline (2001). Data mining: concepts and techniques. Morgan Kaufmann. p. 5.

Multidimensional Approximations

Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course is concerned with interpolation by multidimensional periodic splines associated with certain elliptic differential operators. There will investigate the problem of uniform approximation by multidimensional periodic splines (as basis funnctions).

Recommended literature:

1. WilliFreeden. Interpolation by multidimensional periodic splines. Journal of Approximation Theory, Volume 55, Issue 1, October 1988, Pages 104-117.
2. J. W. S. CASSELS, “An Introduction to the Geometry of Numbers,” Springer-Verlag, Berlin/Heidelberg/New York, 1981.
3. F. J. DELVES AND W. SCHEMPP, On optimal periodic spline interpolation, J. Math. Anal. Appl. 52 (1975), 553-560.
4. J. J. J~NGARRA, J. R. BUNCH, C. B. MOLER, AND G. W. STEWART, “LINPACK User’s Guide,” SIAM, Philadelphia, 1979.
5. W. FREEDEN, On spherical spline interpolation and approximation, Math. Methods Appl. sci. 3 (1981), 551-575.

6. W. FREEDEN, On the permanence property in spherical spline interpolation, The Ohio State University, Department of Geodetic Science, Columbus, OH, OSU Report No. 341, 1982.
7. W. FREEDEN, On spline methods in geodetic approximation problems, Math. Methods Appl. Sci. 4 (1982), 382-396.

Big Data

Lecturer: Dr. Arman Darbinyan
Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (graded)
Standard Studies Period: 2 years

Course description: Big data is a term for data sets that are so large or complex that traditional dataprocessing applications are inadequate to deal with them. Challenges include analysis, capture,data curation, search, sharing, storage, transfer, visualization, querying, updating andinformation privacy. The term "big data" often refers simply to the use of predictive analytics,user behavior analytics, or certain other advanced data analytics methods that extract valuefrom data, and seldom to a particular size of data set.

Recommended literature:

1. Victor Maer-Schoenberger, Kenneth Cuciere. Big Data: A revolution that will change how we live, work and think. - Moscow: Mann, Ivanov and Ferber, 2013.
2. Gaurav Vaish. Getting Started with NoSQL - 2013.
3. A. Blum, J. Hopcroft, R. Kannan. Foundations of Data Science. 2016.
4. Franks B. Per. with English. Baranov A. The Taming of large data: how to extract knowledge from information arrays with the help of deep analytics. - Mann, Ivanov and Ferber, 2014.
5. Maeks D. Per. with English. Mironova P. Key figures. How to earn more using the data that you already have. - Mann, Ivanov and Ferber, 2013.

Computer Vision

Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course provides an introduction to computer vision including fundamentals of image formation, camera imaging geometry, feature detection and matching, multiview geometry including stereo, motion estimation and tracking, and classification.

The focus of the course is to develop the intuitions and mathematics of the methods in lecture, and then to learn about the difference between theory and practice in the problem sets. In this course you do not, for the most part, apply high-level library functions but use low to mid level algorithms to analyze images and extract structural information.

Recommended literature:

1. Richard Szeliski. Computer Vision: Algorithms and Applications. September 3, 2010, Springer.
2. Abdel-Hakim, A. E. and Farag, A. A. (2006). CSIFT: A SIFT descriptor with color invariant characterstics. In IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'2006), pp. 1978–1983, New York City, NY.
3. Baker, S. and Nayar, S. (1999). A theory of single-viewpoint catadioptric image formation. International Journal of Computer Vision, 5(2):175–196.
4. Cham, T. J. and Cipolla, R. (1998). A statistical framework for long-range feature matching in uncalibrated image mosaicing. In IEEE Computer Society Conference on Computer Vision and Pattern Recognition (CVPR'98), pp. 442–447, Santa Barbara.
5. De la Torre, F. and Black, M. J. (2003). A framework for robust subspace learning. International Journal of Computer Vision, 54(1/2/3):117–142.

Framework (R / Python)

Labor intensity: 2 ECTS, 72 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course is an introduction to the Python programming language. We cover data types, control flow, object-oriented programming, and graphical user interface-driven applications. The examples and problems used in this course are drawn from diverse areas such as text processing, simple graphics creation and image manipulation, HTML and web programming, and genomics.

Recommended literature:

1. Kenneth A. Lambert, The Fundamentals of Python: First Programs, 2011, Cengage Learning.

Deep learning

Labor intensity: 3 ECTS, 108 academic hours

Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course is part of a broader family of machine learningmethods based on learning data representations, as opposed to task-specific algorithms. Learning can be supervised, partially supervised or unsupervised.

Some representations are loosely based on interpretation of information processing and communication patterns in a biological nervous system, such as neural coding that attempts to define a relationship between various stimuli and associated neuronal responses in the brain.Research attempts to create efficient systems to learn these representations from large-scale, unlabeled data sets.

Deep learning architectures such as deep neural networks, deep belief networks and recurrent neural networks have been applied to fields including computer vision, speech recognition, natural language processing, audio recognition, social network filtering, machine translation and bioinformatics where they produced results comparable to and in some cases superior to human experts.

Recommended literature:

1. Bengio, Y.; Courville, A.; Vincent, P. (2013). "Representation Learning: A Review and New Perspectives". IEEE Transactions on Pattern Analysis and Machine Intelligence. 35 (8): 1798–1828. arXiv:1206.5538 . doi:10.1109/tpami.2013.50.
2. Schmidhuber, J. (2015). "Deep Learning in Neural Networks: An Overview". Neural Networks. 61: 85-117.
3. Bengio, Yoshua; LeCun, Yann; Hinton, Geoffrey (2015). "Deep Learning". Nature. 521: 436–444.
4. Jürgen Schmidhuber (2015). Deep Learning. Scholarpedia, 10(11):32832.
5. Olshausen, B. A. (1996). "Emergence of simple-cell receptive field properties by learning a sparse code for natural images". Nature. 381 (6583): 607–609.
6. Ciresan, Dan; Meier, U.; Schmidhuber, J. (June 2012). "Multi-column deep neural networks for image classification". 2012 IEEE Conference on Computer Vision and Pattern Recognition: 3642–3649. doi:10.1109/cvpr.2012.6248110.
7. Krizhevsky, Alex; Sutskever, Ilya; Hinton, Geoffry (2012). "ImageNet Classification with Deep Convolutional Neural Networks". NIPS 2012: Neural Information Processing Systems, Lake Tahoe, Nevada.

Neural Networks

Labor intensity: 2 ECTS, 72 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: The course provides a comprehensive foundation to Artificial Neural

Networks and Machine Leaning with applications to Pattern Recognition and Data Mining. Learning processes: supervised and unsupervised, deterministic and statistical. Clustering. Single Layer and multilayer perceptrons. Least-Mean-square, backpropagation, and Al-Alaoui algorithms. Radial-Basis function networks. Committee Machines. Principal component analysis. Self-Organizing Maps. Current topics of interest.

Recommended literature:

1. Hagen, Demuth, and Beale: Neural Network Design, PWS Publishing Company, 1996.
2. J. T. Tou and R. C. Gonzalez: Pattern Recognition Principles, Addison-Wesley.
3. MATLAB Neural Networks Toolbox and Image Processing Toolbox.
4. C. M. Bishop: Neural Networks for Pattern Recognition.
5. Andrew Webb: Statistical Pattern Recognition.
6. Gonzalez, Woods, and Eddins: Digital Image Processing Using MATLAB.

Foreign language

Labor intensity: 5 ECTS, 180 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course will provide instruction in academic and professional language skills for non-native speakers of English. Emphasis is placed on development of integrated language skills for use in studying a particular content area. Upon completion, students should be able to demonstrate improved language skills for participation and success within the particular topic area.

Economic-mathematical methods and models

Lecturer: Dr. Arman Darbinyan
Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: The course builds on the foundation provided in the first level courses in Mathematics and Economics. The concepts in this course provide a solid foundation for the mathematical analysis. Emphasis will be placed on the understanding and application of mathematical concepts rather than just computational skills, the use of algorithms and the manipulation of formula.

Recommended literature:

1. Berezhnaya EV, Berezhnoy VI Mathematical Methods of Modeling Economic Systems - Moscow: Finance and Statistics, 2005.
2. Kuznetsov A.V. Economic-mathematical methods and models. Minsk: BSEU, 1999.
3. Kuznetsov B.T. Mathematics. M .: UNITY-DANA, 2004.
4. Malykhin VI Mathematical modeling of the economy. - Moscow: URAO, 1998.
5. Shikin EV, Chkhartishvili AG Mathematical methods and models in control .: Proc. allowance. - Moscow: The Case, 2000.
6. Wagner G. Fundamentals of Operations Research. - Moscow: The World, 1972.
7. Zamkov OO et al. Mathematical Methods in Economics. - Moscow: DIS, 1998.
8. Kremer N.Sh. Investigation of operations in the economy. M .: UNITI, 1997.
9. Taha X. Introduction to the study of operations: In 2 books. - Moscow: Mir, 1995.

Data Mining 2

Labor intensity: 4 ECTS, 144 academic hours
Form of final control: exam (graded)
Standard Studies Period: 2 years

Course description: The Data Mining programme focuses on modern developments at the intersection of statistics, artificial intelligence and database management. The overall goal of the data mining process is to extract information from a data set and transform it into an understandable structure for further use. Aside from the raw analysis step, it involves database and data management aspects, data pre-processing, model and inference considerations, interestingness metrics, complexity considerations, post-processing of discovered structures, visualization, and online updating.

Recommended literature:

1. "Data Mining Curriculum". ACM SIGKDD. 2006-04-30. Retrieved 2014-01-27.
2. Clifton, Christopher (2010). "Encyclopædia Britannica: Definition of Data Mining". Retrieved 2010-12-09.
3. Hastie, Trevor; Tibshirani, Robert; Friedman, Jerome (2009). "The Elements of Statistical Learning: Data Mining, Inference, and Prediction". Retrieved 2012-08-07.
4. Fayyad, Usama; Piatetsky-Shapiro, Gregory; Smyth, Padhraic (1996). "From Data Mining to Knowledge Discovery in Databases" (PDF). Retrieved 17 December 2008.
5. Han, Jiawei; Kamber, Micheline (2001). Data mining: concepts and techniques. Morgan Kaufmann. p. 5.

NLP

Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: Natural language processing is a major component for building an artificial intelligence system. This course will provide students with the fundamental techniques of natural language processing, an understanding of the limits of those techniques and the current research issues. Students will be able to evaluate various potential applications in natural language processing.

Recommended literature:

1. L. R. Bahl, P. F. Brown, P. V. de Souza, and R. L. Mercer, "A tree based statistical language model for natural language speech recognition," in Acoustics, Speech and Signal Processing, IEEE Transactions on, vol. 37, Issue 7, (Yorktown Heights, NY,USA), pp. 1001–1008, July 1989.
2. P . Clarkson and R. Rosenfeld, "Statistical language modeling using the cmu-cambridge toolkit," in Proceedings EUROSPEECH (N. F.G. Kokkinakis and E. Dermatas, eds.), vol. 1, (Rhodes, Greece), pp. 2707–2710, September 1997.
3. J. Tejedor, R. Garca, M. Fernndez, F. J. LpezColino, F. Perdrix, J. A. Macas, R. M. Gil, M. Oliva, D. Moya, J. Cols, , and P. Castells, "Ontology-based retrieval of human speech," in Database and Expert Systems Applications, 2007. DEXA '07. 18th International Conference on, (Regensburg, Germany), pp. 485– 489, September 2007.
4. J. R. Bellegarda, "Statistical language model adaptation: Review and perspectives," vol. 42, no. 1, pp. 93–108, 2004.
5. Y.-Y. Wang, M. Mahajan, and X. Huang, "A unified context-free grammar and n-gram model for spoken language processing," in IEEE International Conference on Acoustics, Speech, and Signal Processing, vol. III, (Istanbul, Turkey), pp. 1639–1642, Institute of Electrical and Electronics Engineers, Inc., 2000.

Robotics

Labor intensity: 2 ECTS, 72 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This is a beginning course in robotics. We will be utilizing Lego Mindstorm kits, Robolab software and various Lego Robotics materials. The objective of this course is to introduce the student to basic programming as well as problem solving strategies. This course will involve students in the development, building and programming of a LEGO Mindstorm robot. Students will work hands-on in teams to design, build, program and document their progress. Topics may include motor control, gear ratios, torque, friction, sensors, timing, program loops, logic gates, decision-making, timing sequences, propulsion systems and binary number systems.

Recommended literature:

1. http://www.ortop.org/ Oregon Robotics Tournament Outreach Program - Jr. FLL, FLL, FTC resources

2. http://waddlebot.squarespace.com/robotc/ Super easy to build NXT training robot with Robot C learning lessons
3. http://www.education.rec.ri.cmu.edu/ Carnegie Mellon Robotics Academy Training Site
4. Oregon Robotics Tournament and Outreach Program, includes JFLL, FLL, FTC — www.ortop.org
5. By teachers for teachers, several programs — http://www.superquest.net/webclass/sboost/lessonscurriculum/index.htm
6. Robocup — http://www.robocup.org/ — Dr. Elizabeth Sklar has extensive outreach materials, Jo saw her at NCWIT BPC Workshop in June 2009) — http://www.sci.brooklyn.cuny.edu/~sklar/
7. Carnegie Mellon University FIRE Project — http://www.fire.cs.cmu.edu/
8. Botball -- http://www.botball.org/

NLP 2

Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course provides an introduction to the field of Natural Language Processing. It includes relevant background material in Linguistics, Mathematics, Probabilities, and Computer Science. Some of the topics covered in the class are Text Similarity, Part of Speech Tagging, Parsing, Semantics, Question Answering, Sentiment Analysis, and Text Summarization. The course includes quizzes, programming assignments in Python.

Recommended literature:

1. Daniel Jurafsky, James H. Martin (2009). Speech and Language Processing (2nd ed.). Prentice Hall.
2. Covington, M. A (1994). Natural Language Processing For Prolog Programmers. Prentice-Hall.

Practical application in robotics

Labor intensity: 3 ECTS, 108 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course introduces students to robotics within manufacturing systems. Topics include: classification of robots, robot kinematics, motion generation and transmission, end effectors, motion accuracy, sensors, robot control and automation. This course is a combination of lecture and project work, and utilizes industrial robots.

Recommended literature:

1. http://www.ortop.org/ Oregon Robotics Tournament Outreach Program - Jr. FLL, FLL, FTC resources
2. http://waddlebot.squarespace.com/robotc/ Super easy to build NXT training robot with Robot C learning lessons
3. http://www.education.rec.ri.cmu.edu/ Carnegie Mellon Robotics Academy Training Site
4. Oregon Robotics Tournament and Outreach Program, includes JFLL, FLL, FTC — www.ortop.org
5. By teachers for teachers, several programs — http://www.superquest.net/webclass/sboost/lessonscurriculum/index.htm
6. Robocup — http://www.robocup.org/ — Dr. Elizabeth Sklar has extensive outreach materials, Jo saw her at NCWIT BPC Workshop in June 2009) — http://www.sci.brooklyn.cuny.edu/~sklar/
7. Carnegie Mellon University FIRE Project — http://www.fire.cs.cmu.edu/
8. Botball -- http://www.botball.org/

Economy and policy of transition

Lecturer: Prof. Dr. Armen Darbinyan
Labor intensity: 1 ECTS, 36 academic hours
Form of final control: exam (pass/fail)
Standard Studies Period: 2 years

Course description: This course studies the economics of public policy towards the environment. We begin by examining the problem of market failure in the presence of externalities and public goods. Then, we consider the public policy responses to these market failures, including command-and-control regulations, tax and subsidy incentives, marketable pollution permits, voluntary programs, and information as regulation. We consider these policies in contexts such as local pollution, climate change, threats to biodiversity, environmental justice, international trade, and development. In addition, we learn how to measure the costs and benefits of pollution control. By the end of the semester, you will learn how economists think about environmental problems, understand the advantages and disadvantages of a range of environmental policies, be able to conduct a cost-benefit analysis, and have a complete economic analysis of an environmental problem.